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Research Article

A Real-Time Tourism Route Recommendation System Based on Multitime Scale Constraints

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In order to increase the capability of real-time intelligent recommendation of tourists' information on cross-regional city-level tourist routes with epidemic normalization, a real-time intelligent recommendation algorithm for cross-regional city-level tourist routes with epidemic normalization based on multi-time scale constraints is proposed. Under the training of limited samples, the tourist correlation model of the epidemic normalization of cross-regional city-level tourist routes is created. In addition, two kernel functions i.e. the mixed and the global are assembled to excerpt the correspondence features of the epidemic normalization cross-regional city-level tourist route recommendation information. As a result, the well-known particle swarm optimization (PSO) procedure and algorithm with multitime scale constraints are adopted to carry out the adaptive learning of the epidemic normalization cross-regional city-level tourist route recommendation, and the convergence control of the recommended method is comprehended through mining the geographic information data sets of cities. This paper analyzes the universality and ergodicity of tourists' personal interest preferences and social characteristics in urban tourism and combines a gradient algorithm to carry out particle swarm evolution and self-adaptive optimization for the recommendation of cross-regional city-level tourist routes with a normalized epidemic situation, so as to realize the group real-time intelligent recommendation of tourists' information on cross-regional city-level tourist routes with the normalized epidemic situation. The model outcomes indicate that the exactitude and precision of cross-regional city-level tourism route information recommendation with this algorithm are decent, and the convergence of the swarm intelligence optimization (SIO) problem is robust, which can circumvent dipping into the local optimal solution in the process of real-time intelligent recommendation of tourism routes and improve the intelligence and global stability of cross-regional city-level tourism route recommendation with epidemic normalization.

1. Introduction

With the speedy improvement of the economy, the public's corporeal standard has enriched obviously, and to a greater extent, people begin to pay attention to rich spiritual life, which promotes the development of tourism. However, under the background of epidemic normalization prevention and control, it brings great challenges to the tourism industry. At present, people mainly search for travel information on the Internet to customize their travel plans, but the information overload problem on the Internet is becoming more and more serious, so it is necessary to establish a model for recommending cross-regional city-level travel routes with epidemic normalization. Combining the distribution characteristics of cross-regional city-level travel routes with epidemic normalization, the reliability of recommending cross-regional city-level travel routes with network modeling big data cost analysis can be improved [1]. Therefore, to a greater extent, academics begin to recompense consideration to the exploration of travel route planning. Most tourists will be restricted by many factors such as traffic, expenses, time, scenic spots, and hotels. When making travel plans. However, the existing research does not fully consider tourists' preferences and constraints, and it is difficult to really meet the individual needs of tourists [2].

The normalized cross-regional city-level tourist routes are realized by a personalized network of independent education and statistics facilities rendering to tourists' personal predilections. Tourists' statistics and knowledge resource information on the normalized cross-regional city-level tourist routes want to be boosted, categorized, and kept adaptively rendering to the tourists' predilections [3]. The resource scheduling and personalized recommendation of the normalized cross-regional city-level tourist routes are combined with the multisource distributed design method to improve the resource scheduling ability of the normalized cross-regional city-level tourist routes and the ability to extract tourists' urban tourism interests and preferences [1]. In the cross-regional city-level tourist routes with complex epidemic normalization, personalized recommendation and resource optimization scheduling are carried out for complex and diverse online learning resources rendering to the tourists' past visit archives and predilections, so as to encourage the information practice and progress the energetic communication aptitude of the cross-regional city-level tourist routes with epidemic normalization [4]. It is of countless implications to revise the personalized real-time intellectual recommendation procedure of cross-regional city-level tourist routes with epidemic normalization in the optimization design of cross-regional city-level tourist routes with epidemic normalization. In the traditional methods, the personalized endorsement and communal detection approach for cross-regional city-level tourist routes with normalized epidemic situations mainly comprise intelligent PSO procedure, data clustering recommendation system, association rule-based mining process, and fuzzy PID recommendation procedure, etc., and the topological structure of cross-regional city-level tourist routes is optimized according to multilevel epidemic situation normalization [5].

Combining the appropriate features of the recommendation tasks and information sharing, a data clustering center for a personalized recommendation of epidemic normalization cross-regional city-level tourist routes is established, and an algorithm for a recommendation of epidemic normalization cross-regional city-level tourist routes is designed by using association rule mining method, so as to develop and progress the personalized appearance aptitude of epidemic normalization cross-regional city-level tourist routes. Related literature has designed the recommendation algorithm for epidemic normalization cross-regional city-level tourist routes, and achieved certain research results. Among them, in [6] it is proposed based on a community discovery algorithm of epidemic normalization cross-regional city-level tourist routes based on parallel recommendation, compelling the tourist manners value, tourist ingesting value, and faithfulness of the epidemic normalization cross-regional city-level tourist routes as independent variables. The fuzzy decision-making model for public detection of the epidemic normalization cross-regional city-level tourist routes is established, and the optimization design of the epidemic normalization cross-regional city-level tourist route recommendation model is carried out by combining the association mining method. Nevertheless, the calculation cost of this technique is enormous, and the real-time performance of the epidemic normalization cross-regional city-level tourist route recommendation is not good.

In [7], a community discovery and recommendation algorithm of epidemic normalization cross-regional city-level tourist routes founded on the transformation factor assessment and intellectual and adaptive PSO is proposed. The synchronization tag of epidemic normalization cross-regional city-level tourist routes communities is established, the community association attribute features of epidemic normalization cross-regional city-level tourist routes are extracted, and the association amongst the interaction degree within groups and recommendation consequence is investigated. To realize personalized recommendations of cross-regional city-level tourist routes for epidemic normalization, this method has poor intelligence in the process of recommending cross-regional city-level tourist routes for epidemic normalization, and its global optimization ability is not strong [8].

To elucidate the aforementioned difficulties, in this paper we suggest a real-time intelligent recommendation algorithm for cross-regional city-level tourist routes based on multitime scale constraints. Firstly, under the training of limited samples, the tourist correlation model of the epidemic normalization cross-regional city-level tourist routes is created, and the two kernel functions, i.e., the mixed and the global are assembled to excerpt the association features of the epidemic normalization cross-regional city-level tourist route recommendation information, and the well-known PSO procedure with multitime scale constraints is adopted to carry out the adaptive learning of the epidemic normalization cross-regional city-level tourist route recommendation. At that moment, the convergence control of the recommended procedure is comprehended through mining the geographic information data sets of cities, and the universality and ergodicity of individual tourists' urban tourism interest preferences and social characteristics are analyzed. Combined with the gradient algorithm, the particle swarm evolution and self-adaptive optimization of the epidemic normalization cross-regional city-level tourist route recommendation are carried out, and the real-time intelligent recommendation of the epidemic normalization cross-regional city-level tourist route information is recognized. As a final point, the simulation exploration illustrates the loftier performance of the anticipated technique in enlightening the personalized real-time intelligent recommendation ability of cross-regional city-level tourist routes with the normalized epidemic situation. The following are some of the fundamental contributions of our work:

(1) We propose a real-time intelligent recommendation algorithm for cross-regional city-level tourist routes based on multitime scale constraints

(2) The tourist correlation model of the epidemic normalization cross-regional city-level tourist routes is assembled, and two kernel functions, i.e., the mixed and the global are created

(3) The particle swarm optimization algorithm with multitime scale constraints is adopted to carry out the adaptive learning of the epidemic normalization cross-regional city-level tourist route recommendation

The remaining manuscript is systemized in the subsequent fashion. In section 2, we discuss the tourism recommendation information model and correlation feature extraction. The recommended algorithm optimization process is deliberated in section 3. The simulation experiment and result analysis are validated in section 4. As a final point, section 5 recaps the manuscript and talks about promising future research.

2. Model for Tourism Recommendation and Extraction of Correlation Features

2.1. Recommended Information Transfer Model of Urban Tourist Routes. In order to comprehend the personalized recommendation and characteristics identification of epidemic normalization cross-regional city-level tourist routes, the parallel recommendation procedure is practiced to excerpt the tourists' interest preferences and mine statistics, and a hybrid system of the mixed and global kernel functions is assembled to excerpt related structures of epidemic normalization cross-regional city-level tourist route recommendation information. The fuzzy decision function of epidemic normalization cross-regional city-level tourist route recommendation evidence is acquired through the restricted sample training. This should be noted that the self-organizing nonlinear mapping, which is denoted by $\Phi: x \in R^n \longrightarrow F$, is created to characterize the information transmission space of epidemic normalization cross-regional city-level tourist routes, and the recommended information of epidemic normalization cross-regional city-level tourist routes is mapped to high-dimensional feature space by combining fuzzy decision-making and intelligent swarm optimization [9–11]. In fact, this is expected that the recommended sample set for training of cross-regional city-level tourist routes with the normalized epidemic situation is $x_i \in R^n$, in which the personalized characteristic quantity $\{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$ of cross-regional city-level tourist routes exemplifies the input vector of the anticipated recommendation system, $y_i \in R^n$ is the target quantity worth for the personalized recommendation of cross-regional city-level tourist routes, and $x_i \in R^n$ is the sample number of cross-regional city-level tourist routes. Collective with the association rule mining procedure, the objective function of the anticipated real-time intelligent and adaptive recommendation system of cross-regional city-level tourist routes with the normalized epidemic situation is as follows:

$$\begin{aligned} &\text{minimize} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} (\xi_i + \xi_i^*),\\ &\text{subject to } y_i - (w'\Phi(x_i) + b) \le \varepsilon - \xi_i,\\ &(w'\Phi(x_i) + b) - y_i \le \varepsilon - \xi_i^*,\\ &\xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, n; C > 0. \end{aligned} \tag{1}$$

Wherein ξ_i and ξ_i^* exemplify the semantic ontology attributes, characteristics, and features and the corresponding association rule variables of cross-regional city-level tourist routes distribution. The generalized learning procedure is implemented to carry out and perform adaptive learning in the development of cross-regional city-level tourist routes recommendation, which is the cost factor recommended for cross-regional city-level tourist routes, and is implemented to understand the punishment control of wrong and incorrect samples. Note that, by adopting the PSO control, the dissimilarity function of the personalized recommendation of cross-regional city-level tourist routes is as follows:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b. \tag{2}$$

Wherein α_i and α_i^* are the recommended attribute values and template category numbers of cross-regional city-level tourist routes, respectively. In addition, the variable $K(x_i, x_j)$ is a symmetric kernel function, in fact, sustaining the Mercer circumstance, and b represents the recommended threshold of cross-regional city-level tourist routes.

This should be noted that each data tuple's feature vector set is built, and a hybrid kernel function is created by using the local kernel function (RBF kernel function) and the global kernel function (polynomial kernel function) as control decision functions for the recommendation of cross-regional city-level tourist routes with a normalized epidemic situation, and its expression is as follows:

$$K_{\min} = \beta K_{poly} + (1 - \beta) K_{rbf}, \beta \in (0, 1). \tag{3}$$

Wherein $K_{poly} = [(x \cdot x_i) + 1]^2$ represents the fuzzy personalized feature distribution kernel function recommended by cross-regional city-level tourist routes, and $K_{RBF} = \exp(-\gamma\|x - x_i\|^2)$ represents the RBF kernel function of confidence trustworthiness of cross-regional city-level tourist routes with the normalized epidemic situation. In fact, its purpose is to adjust the impact of both kernel functions over the whole mixed kernel function, which is also known as, the weight coefficient. Therefore, an information transmission model for the recommendation of cross-regional city-level tourist routes with a normalized epidemic situation is constructed, and the tourist characteristics of cross-regional city-level tourist routes with a normalized epidemic situation are extracted and personalized recommendation design is carried out by combining the hybrid optimization method of particle swarm optimization [12].

2.2. Extraction of Correlation Features of Recommended Information of Tourist Routes. Over the foundation of assembling both the hybrid and the universal kernel functions, this paper extracts the correlation features of the recommended information of cross-regional city-level tourist routes with a normalized epidemic situation and adopts the data set mining of urban geographic information to realize the convergence control of the recommendation process, so as to obtain the potential tourist variables of cross-regional city-level tourist routes with a normalized complex epidemic situation, which are expressed as: $\{S_1, S_2, \cdots, S_L\}$ by four tuples. Taking the tourism interest preference and the distribution of urban geographic and cultural information resources as control constraints, the characteristic abstraction conveyance regulator prototype of the personalized recommendation system for the cross-regional city-level tourist routes is as follows:

$$\alpha^i_{\text{desira}} = \alpha_1 \cdot \frac{\text{Density}_i}{\sum_{\text{i}} \text{Density}_i} + \alpha_2 \frac{AP_i}{AP_{\text{init}}}, \tag{4}$$

where in

$$\begin{cases} \alpha_1 + \alpha_2 = 1, \alpha_1, \alpha_2 \in [0, 1], \\ \alpha_2 = \dfrac{\max_{\text{i}} (AP_i) - \min_{\text{i}} (AP_i)}{AP_{\text{init}}}. \end{cases} \tag{5}$$

The aforementioned two formulas, in fact, symbolize the sparse coefficient from relay node U to the monitoring node of cross-regional city-level tourist routes with a normalized epidemic situation, where $M_i [t_l > M_m \vee M_n$, $M_m [t_m > M_j$, $M_n [t_n > M_j$, represents the scoring explanatory variable of recommended information of cross-regional city-level tourist routes, and $N_2(u) = \{v | d_G(u, v) = 2\}$ exemplifies the average mutual information of tourist characteristics U of cross-regional city-level tourist routes with a normalized epidemic situation, where $(i \neq m \neq n \neq j, a \neq b \neq c)$. Under the constriction controller of connotation instructions, the prospective association features of cross-regional city-level tourist routes with a normalized complex epidemic situation are obtained using the following equation:

$$\varepsilon_t(i, j) = \frac{\alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N}} \alpha_t(i) a_{ij} b_j(o_{t+1}) \beta_{t+1}(j), \tag{6}$$

wherein $|\text{Re}v(u)|$ represents the characteristic distribution point set of cross-regional city-level tourist routes, $\text{Re}v(u)$ represents the number of tourist nodes, a_{ij} represents the tourist scoring measurement information of cross-regional city-level tourist routes with a normalized epidemic situation, b_j represents the joint mutual information recommended by cross-regional city-level tourist routes, and $Or\,de\,r(\text{Re}v(u))$ represents the matching degree of nodes in the distribution space of cross-regional city-level tourist routes according to their personalized behavior characteristics. Uniting the connotation rule constraints and the chaotic mapping, the self-adaptive clustering of cluster intelligence information of cross-regional city-level tourist routes is carried out, and the recommended cluster output of cross-regional city-level tourist routes is gotten as mathematically illustrated in the following equation:

$$\begin{aligned} f_{\text{lg}-M}(z) &= \left(f_{\text{lg}}(z), f_{\text{lg}-x}(z), f_{\text{lg}-y}(z)\right) \\ &= \left(f_{\text{lg}}(z), h_x * f_{\text{lg}}(z), h_y * f_{\text{lg}}(z)\right). \end{aligned} \tag{7}$$

Note that in the above equation, the notation $f_{\text{lg}}(z)$ exemplifies the score value of tourist items recommended by cross-regional city-level tourist routes with a normalized epidemic situation, thus obtaining the quadruple expression of correlation feature extraction of cross-regional city-level tourist routes with the normalized epidemic situation as follows:

$$\begin{aligned} &\max \left\{ |Ch(u) - Ch(u) \cap Ch(u_2)| + |Ch(u) \cap Ch(u_2)| \right. \\ &\quad \left. |Ch(u_2) - Ch(u) \cap Ch(u_2)| + |Ch(u) \cap Ch(u_2)| \right\} \\ &\quad = \max \left\{ |Ch(u)|, |Ch(u_2)| \right\} \leq \Delta. \end{aligned} \tag{8}$$

In the above formula, $Ch(u)$ represents the association rule coefficient of cross-regional city-level tourism route recommendation, and node v is added to $R2(u)$ in order to comprehend and understand the dynamic characteristic abstraction of personalized tourist features and characteristics [13].

3. Optimization of the Recommendation Algorithm

3.1. The Gradient PSO Procedure. Over the foundation of assembling a hybrid system which is in fact from the mixed and the global kernel function to excerpt the correlation features of the recommendation statistics of epidemic normalization cross-regional city-level tourist routes, an improved design of the real-time intelligent recommendation algorithm for epidemic normalization cross-regional city-level tourist routes is proposed in this paper. For the multiconstraint multiobjective tourist route planning problem, if only the objective function is weighted, the global optimal solution may not be obtained, so this paper practices the enhanced greedy set of rules to elucidate the optimal tourist routes. In the actual tourism scene, tourists are more thinking about which scenic spot is suitable to go next when the current scenic spot is finished. The greed algorithm is one of the most commonly used algorithms to solve the problem of route planning. However, in this paper, aiming at practical problems, an improved greedy algorithm is used to recommend the top M routes with the highest scores for tourists to choose [14].

The improved greedy algorithm is described as follows: tourists start from the recommended hotel, only consider the top N scenic spots with the highest constraint score based on their current location, and only consider the scenic spots they have never visited. Because tourists have to return to the hotel, when tourists visit all the scenic spots and finally return to the hotel, the hotel constraint score of 10I is no longer considered. So we can get M routes, calculate the total score of each route, and finally only keep the top M routes with the highest total score for tourists to choose from. Set the objective function to maximize the total score of the route and the number of types of scenic spots under the condition of satisfying the user constraints. Taking advantage of the initial value sensitivity, regularity, universality, ergodicity, and other advantages of a chaotic map, the universal optimization regulator of the recommended procedure is performed, and as an outcome, the Logistic map is assembled, whose manifestation is mathematically given in the following equation:

$$y_i = \mu y_i (1 - y_i), \tag{9}$$

wherein $y_i \in [0, 1]$ is the random number, μ is the group real-time intelligent recommendation control parameter of cross-regional city-level tourist routes with the normalized epidemic situation. Generally, it takes a value of 4, and a gradient particle swarm algorithm is constructed. d is assumed that in a dimensional gradient particle swarm search space, m represents the population composed of particles and $S = \{P_1, P_2, \cdots, P_m\}$ represents the clustering center of tourists' urban tourism interest preference intelligent search particles in the current dimensional solution space [16]. It represents the current optimization speed of the traversing particle $P_i^d(t)\,(i = 1, 2, \cdots, m)$ of the cross-regional city-level tourism route with the normalized epidemic situation, and $P_{best}^d(t)$ characterizes the paramount position which is practiced by the particle $V_i^d(t)\,(i = 1, 2, \cdots, S)$ itself. The personalized recommendation gradient particle swarm optimization expression of the cross-regional city-level tourism route with the normalized epidemic situation is obtained as follows:

$$\begin{cases} V_i^d(t+1) = W \cdot V_i^d(t) + C_1 \cdot R_1 \cdot \left(P_{\text{best}}^d(t) - P_i^d(t)\right) \\ +C_2 \cdot R_2 \cdot \left(G_{\text{best}}^d(t) - P_i^d(t)\right), \\ P_i^d(t+1) = P_i^d(t) + V_i^d(t+1), \end{cases} \tag{10}$$

wherein $V_i^d(t)$, $V_i^d(t+1)$, $P_i^d(t)$, $P_i^d(t+1)$ is the transmission coefficient and correlation dimension feature quantity of tourists' urban tourism interest preference mining on the cross-regional urban level tourism routes at the current moment and the next moment of the particle, respectively. In addition, the route with the highest total score is a learning factor for tourists, and W is generally between 25 and 25. Similarly, the variables C_1 and C_2 represent the search radius and global search threshold of gradient particle swarm optimization, respectively, when assuming taking random numbers between [0, 1]. It is the inertia weight of the route with the highest total score for tourists' preference. Combined with gradient PSO, the step length of the optimization modification, which is iterative, of the recommended procedure of epidemic normalization cross-regional city-level tourist routes is performed [17]. This should be noted that for each interval the modification formula of the real-time intellectual recommendation system for the epidemic normalization of cross-regional city-level tourist routes is obtained as follows:

$$W(t+1) = 4.0W(t)(1 - W(t)), \tag{11}$$

$$W(t) = W_{\min} + (W_{\max} - W_{\min})W(t), \tag{12}$$

wherein the notation $[W_{\min}, W_{\max}]$ is the range values for the inertia weight factor recommended for cross-regional city-level tourist routes indicating the normalization of the epidemic situation, generally taking (0.5, 0.6).

3.2. Implementation of Real-Time Intelligent Recommendation Algorithm for Tourism Route.

The particle swarm optimization algorithm with multitime scale constraints is used to carry out adaptive learning of cross-regional city-level tourism route recommendations for epidemic normalization [14]. The convergence regulator of the recommendation development is comprehended by mining the geographic information data set of cities, and chaos is familiarized within the process of the optimization in terms of the inertia factor W. In the gradient PSO learning process of cross-regional city-level tourism route recommendation for epidemic normalization, search radius R_1 and R_2 are introduced, and the updated formula is as follows:

$$R_i(t+1) = 4.0R_i(t)(1 - R_i(t)), \tag{13}$$

wherein $R_i(t) \in (0, 1), i = 1, 2$, rendering to the gathering of the tourists, the fuzzy feature measure of epidemic normalization cross-regional city-level tourism route distribution is pulled out, the chaos is familiarized into the two learning factors, as denoted by C_1 and C_2, and the learning formula for recommending epidemic normalization cross-regional city-level tourism route is updated as follows:

$$C_i(t+1) = 4.0C_i(t)(1 - C_i(t)), \tag{14}$$

$$C_i(t) = C_{\min} + (C_{\max} - C_{\min})C_i(t), \tag{15}$$

wherein $i = 1, 2$, $[C_{\min}, C_{\max}]$ is the preliminary population prototype for the gradient PSO. After a scenic spot is played, the top N scenic spots with higher scores are searched as the next scenic spots to be played according to the current scenic spots, and whether joining the scenic spot meets the time constraint and cost constraint of tourists is calculated. If not, the scenic spot is abandoned [18]. If all scenic spots no longer meet the time or cost constraint of tourists, the convergence control coefficient obtained after the tourists' play is defined as illustrated mathematically in the following equation:

$$\delta^2 = \sum_{i=1}^{m} \frac{F_i - F_{\text{avg}}}{F}. \tag{16}$$

Wherein m is the number of particles in the recommended particle swarm of the cross-regional city-level tourism route with a normalized epidemic situation, F_i is the adaptability of particle i to tourists' learning of urban tourism interest preference on the cross-regional city-level tourism route with a normalized epidemic situation, F_{avg} is the average adaptability of the particle swarm, and F is the recommended control objective function, which is used to limit the size of δ^2, and is expressed as follows:

$$F = \begin{cases} \max\limits_{1\le i\le m}\left|F_i - F_{avg}\right|, & \max\limits_{1\le i\le m}\left|F_i - F_{avg}\right| > 1 \\ 1, & \text{其他} \end{cases}. \tag{17}$$

If $\delta^2 <$ H, H is a given constant, the precocious judgment and adaptive processing of tourists' characteristics mining on the cross-regional city-level tourist routes with a normalized epidemic situation are carried out. For the particles falling into a precocious state, the gradient reduction method is adopted to make them jump out of the local optimum, and the realization of this algorithm is described as follows:

$$V_i^d(t+1) = 4.0V_i^d(t)\left(1 - V_i^d(t)\right), \tag{18}$$

$$V_i^d(t) = V_{\min} + \left(V_{\max} - V_{\min}\right)V_i^d(t), \tag{19}$$

wherein $[V_{\min}, V_{\max}]$ is the range of particle velocity of self-adaptive recommendation for cross-regional city-level tourist routes with epidemic normalization [18]. By using the connotation regulation taking out and the local optimization controller methods, the updated formula of recommendation for cross-regional city-level tourist routes with epidemic normalization is obtained as follows:

$$\begin{cases} V_i^d(t+1) = W(t)\cdot V_i^d(t) + C_1(t)\cdot R_1(t)\cdot\left(P_{best}^d(t) - P_i^d(t)\right) \\ +C_2(t)\cdot R_2(t)\cdot\left(G_{best}^d(t) - P_i^d(t)\right), \\ P_i^d(t+1) = P_i^d(t) + V_i^d(t+1). \end{cases} \tag{20}$$

In the above formulas, $t = 1, 2, \cdots, T$ and T represent the maximum iteration times of the population. The convergence regulator of the recommended method is comprehended by mining the geographic information data set of the city. In order to show the system better, it is supposed that the tourist chooses the hotel scenic spot as shown in Figure 1, and the tourist stays in Hotel H, and the tourist expects to get the maximum tourism income. According to the above scenic spots A, B, C, and D, which route should he choose to play, he can get the maximum income while meeting the time constraint of tourists for 8 hours, and the cost constraint is 300 yuan. Assume that $n = 2$, that is, when the greedy algorithm is used, each scenic spot expands downwards into two scenic spots, and the number of routes with the highest revenue output, at last, does not exceed three. According to the threshold judgment result, whether the convergence criterion is satisfied or not is judged and appropriate decisions are made.

The particle swarm optimization and self-adaptive optimization are carried out for the recommendation of epidemic normalization cross-regional city-level tourist routes combined with a gradient algorithm [19]. The convergence regulator of the recommended procedure is comprehended by mining the city's geographic information data set, and the universality and ergodicity of individual tourists' urban tourism interests and social characteristics are investigated. In fact, the PSO and the process of self-adaptive optimization are carried out for epidemic normalization cross-regional city-level tourist routes combined with gradient algorithm, so as to comprehend the real-time intelligent recommendation of tourists' information on epidemic normalization cross-regional city-level tourist routes [20].

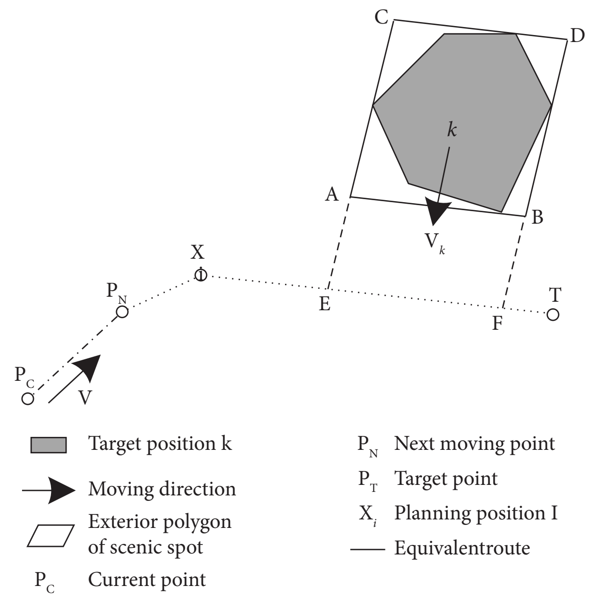

Figure 1: Schematic diagram of recommendation model of hotels and scenic spots selected by tourists.

4. Simulation Experiment, Results, and Discussion

In order to validate the accuracy and convergence of the anticipated technique in the real-time intelligent recommendation of cross-regional city-level tourist routes for the normalization of the epidemic situation, a simulation experiment was conducted. The system includes eight functional modules, including login and registration, the introduction of hotel attractions, preference constraint selection, tourist route planning, hotel information management, route, itinerary management, user information management, and scenic spot information management. Users who want to use the intelligent planning system for tourist routes must register first, and then they can log in after successful registration. After entering the system, users can first choose the information of the scenic spots they are interested in to browse [21]. Secondly, users can come to the preference constraint selection module, enter their own personalized constraints, including travel time, travel expense budget, and the conditions of favorite hotels and scenic spots, and submit them to the background server.

The server in the background will obtain the personalized constraints of users, recommend the hotels and scenic spots with the highest scores for users according to the model established above, and then plan a number of tourist routes for users to show to them with the maximum profit.

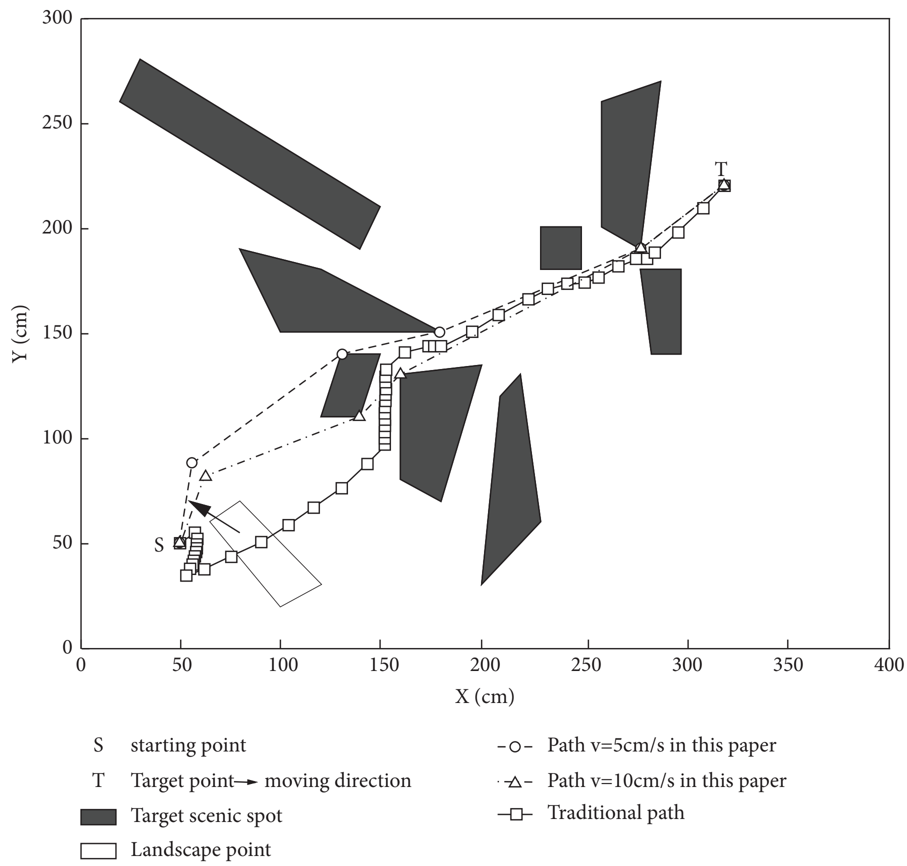

Figure 2: Normalization of epidemic situation. Cross-regional city-level tourist routes.

Users can also manage their past itineraries anytime and anywhere. Administrators have the authority to add, delete and check the information of hotel and scenic spot users, the quantity of tourists that were verified is 2,000, the trial function of the PSO is assumed as type and combination of the ZDT series test functions, the amount of all particles in a particular particle group in D-dimensional universe is 20, the recommended simulation time is 1.3 s, and the iteration is carried out for 6,000 times. The mining results and findings of tourists' urban tourism interest preferences on the cross-regional city-level tourist routes with a normalized epidemic situation are shown in Figure 2.

With the method of this paper, the real-time recommendation method of tourist routes based on multitime scale constraints is adopted, and the result of route optimization recommendation is shown in Figure 3.

Taking the results of route optimization and recommendation in Figure 3 as the input test sample set for tourists' urban travel interest preference for the epidemic-normalized cross-regional city-level tourism route, the adaptive learning of the epidemic-normalized cross-regional city-level tourism route recommendation was performed, and the curve of the convergence was acquired as made known in Figure 4.

According to the analysis of Figure 4, the self-adaptive learning ability of real-time intelligent recommendation of epidemic normalization cross-regional city-level tourist routes by this method is strong, and the universality and ergodicity of urban tourism interest preference and feature mining of epidemic normalization cross-regional city-level tourist routes are good. Additional test the errors of dissimilar approaches in recommending cross-regional city-level tourist routes for epidemic normalization, and get the comparison results as given away in Figure 5. The examination of the results in Figure 5 displays that the accuracy of this method in recommending the information of cross-regional city-level tourist routes with epidemic normalization is decent, and the nondivergence of the swarm aptitude optimization is significantly robust so that the real-time intelligent recommendation process of cross-regional city-level tourist routes with epidemic normalization can be avoided from falling into a local optimal solution.

On this basis, the formulation of tourists' travel plans first needs to determine the tourist attractions they want to visit and the hotels they stay in. Based on this, this paper sets up a hotel attraction scoring model, sets tourists' preference design for hotels and attractions, integrates the information of related hotel attractions, and according to the preference information input by tourists, puts a good hotel and attractions for tourists to choose. In this way, there is no need for tourists' past travel data, so there is a problem of "moving after a cold." This paper also establishes a multi-constraint and multi-objective tourism route planning model. After tourists have determined their tourist attractions and hotels,

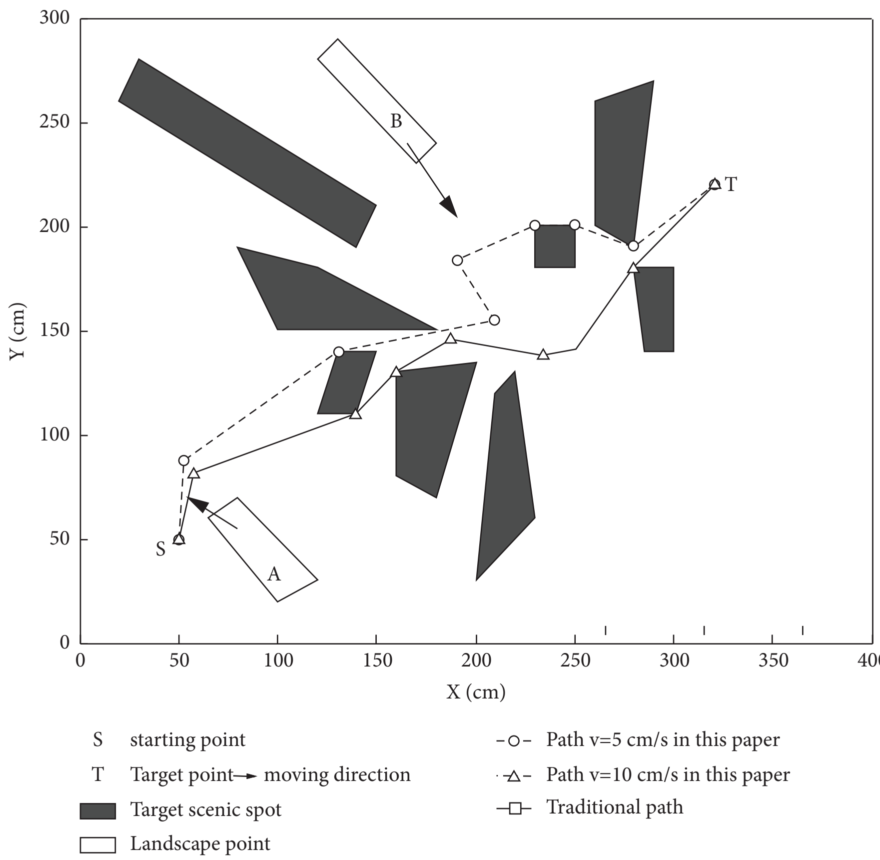

Figure 3: Route optimization recommendation results.

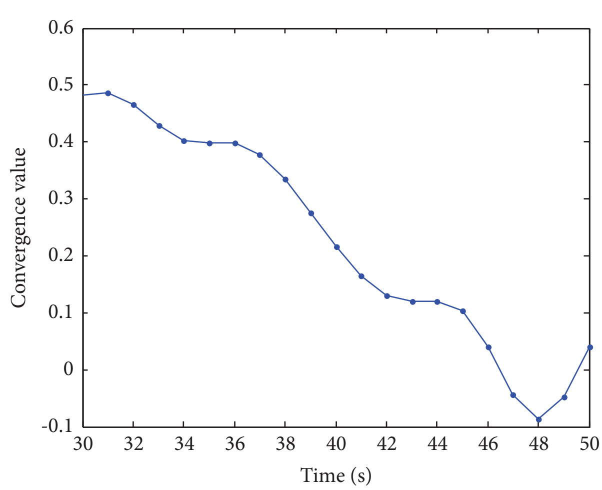

Figure 4: The learning curve of real-time intelligent recommendation of cross-regional city-level tourist routes after epidemic normalization.

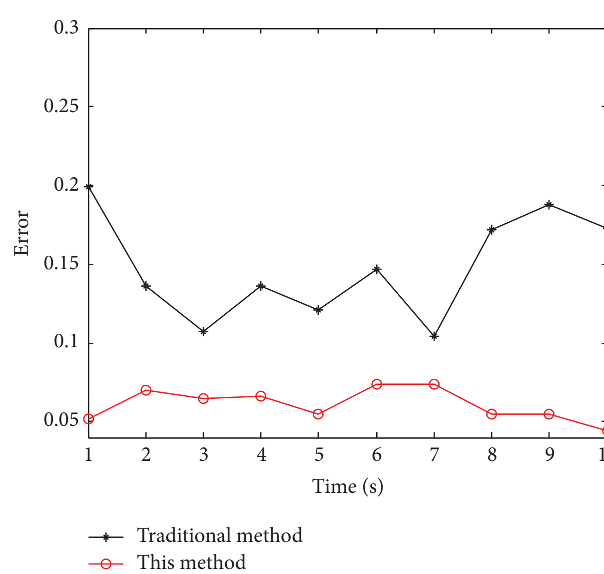

Figure 5: Error comparison of recommendation of cross-regional city-level tourist routes in normalization of the epidemic situation.

the next problem they face is how to determine their tour order [22]. According to the actual needs of tourists, this paper puts forward a tourism route planning model, which sets the starting point and ending point of tourism to be hotels, practices the enhanced greedy procedure and set of rules to solve the model, and finally, obtains the most profitable tourism routes. The model fully considers the realistic factors and has certain rationality and usability.

5. Conclusions and Future Work

According to tourists' historical visit records and preferences, personalized recommendations and resource optimization scheduling can be carried out to promote the information use of cross-regional city-level tourist routes with the normalized epidemic situation. This paper proposes a real-time intelligent recommendation algorithm for cross-regional city-level tourist routes with the normalized epidemic situation based on multitime scale constraints. Under the training of limited samples, the tourist correlation model of epidemic normalization cross-regional city-level tourist routes is constructed, and the correlation features of epidemic normalization cross-regional city-level tourist routes recommendation information are extracted. In addition, subsequently, the convergence governor of the recommended procedure is comprehended by mining the city's geographic information data set, and the universality and ergodicity of tourists' individual urban tourism interest preferences and social characteristics are examined. In fact, the particle swarm evolution and dynamic optimization of epidemic normalization cross-regional city-level tourist routes recommendation are performed by combining the gradient process, so as to comprehend the real-time intelligent endorsement of epidemic normalization cross-regional city-level tourist routes. The research shows that the accuracy of information recommendation of epidemic normalization cross-regional city-level tourist routes by the anticipated process is decent, and the antidivergence of the swarm intelligence optimization is significantly robust so that the real-time intelligent recommendation process of epidemic normalization cross-regional city-level tourist routes can be avoided from dwindling into local optimal solution, and the intelligence and global stability of epidemic normalization cross-regional city-level tourist routes recommendation are enhanced. In fact, this has virtuous application significance in a real-time intellectual recommendation, as well as, in the personalized learning of epidemic normalization cross-regional city-level tourist routes [15].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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